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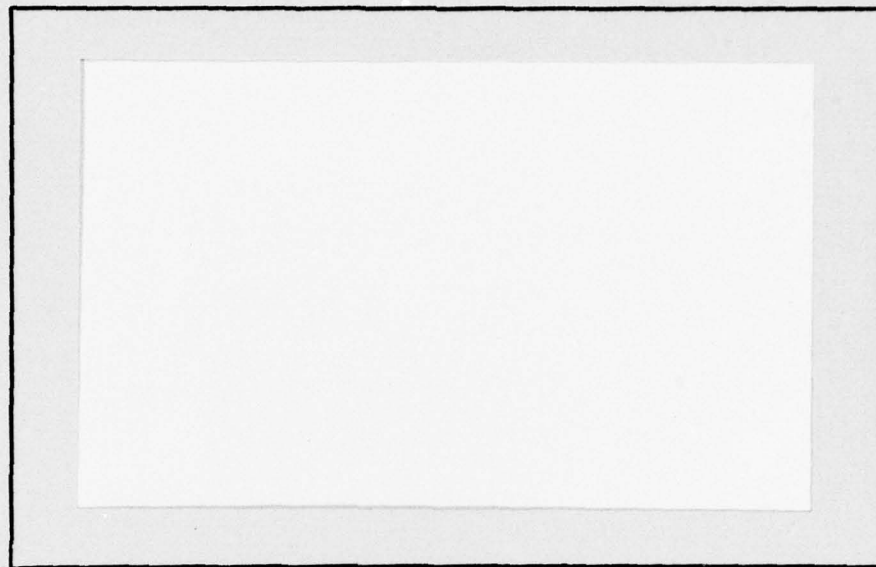
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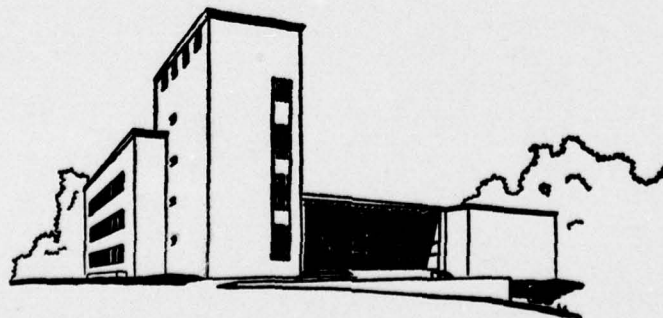
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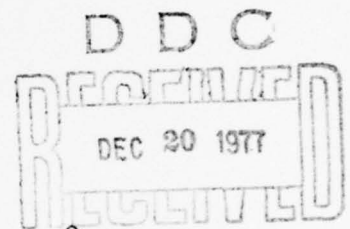
AN EXPERIMENT ON  
EXECUTIVE DECISION MAKING

by

Eduard J. Fidler\* and Gerald L. Thompson\*

July, 1977

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## ABSTRACT

## AN EXPERIMENT ON EXECUTIVE DECISION MAKING

by

Eduard J. Fidler and Gerald L. Thompson  
Carnegie-Mellon University

This paper analyzes capital budgeting decisions of business executives in an experimental setting. Two different data analysis techniques, a linear programming and a maximum likelihood method, are used to analyze preference judgments for hypothetical investment projects. For each of the twenty investment projects the following information was provided: a probability distribution of returns on investment, the magnitude of the investment, the number of additional men to be hired for implementing the investment, and the expected payback period for the investment. Five conclusions are demonstrated based on two independent experiments with business executives:

- (1) Mean return on investment, and payback period, are the most important investment characteristics;
- (2) Upper and middle management executives have almost identical preference structures;
- (3) Downside variation of the return distribution has a stronger influence on investment decisions than overall variation;
- (4) Usefulness of this methodology for (i) analyzing preference judgments of individual executives; (ii) training purposes; and (iii) as an aid to organizational decision making;
- (5) Both data analysis techniques give highly similar conclusions.

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## 1. INTRODUCTION

One of the most common executive decisions involves the acceptance or rejection of investment projects. Surprisingly, there have been few empirical analyses of these decisions. Those that have been reported typically use survey methods to determine the relative use of different capital budgeting and risk evaluation techniques. (e.g., Fremgen [8], Klammer [10], and Petty, Scott, and Bird [15]). Although these studies report which techniques executives use for evaluating capital investments, they do not examine how executives combine the results obtained by these techniques into an overall preference judgment for investment projects.

Two studies which have attempted to address this latter issue were those of Mao [13] and Conrath [3]. In the former, the author used interviews with business executives in eight medium and large companies to investigate (1) the risk analysis employed in investment decisions and (2) the criteria for investment selection. Concerning the concept of risk Mao reported that "...when the investment decision involves only a small portion of the resources of the company, risk is primarily considered to be the prospect of not meeting some target rate of return. However, when the investment concerns a large portion of the company's resources, risk also involves the danger of insolvency." [p.354]. Risk is incorporated into the selection procedure primarily by means of the risk adjusted discount rate approach, where the projected outcome is modified by considering new financial information (e.g., how well is the project justified, who supports the project, etc.), and by introducing a contingency plan. Concerning investment criteria, Mao found: "Payback period is primarily a risk measure. Accounting profit, since this is what the financial community focuses

on, is especially important if the company is widely held and relies on external sources of financing. Internal rate of return is most likely to be the major criterion in closely held firms which are less worried by erratic patterns in their per share earnings, which finance themselves, and which make many small investments so that the risk in any one investment is not critical." [p. 359]

Conrath [3] obtained similar results via a rather simple clinical experiment with nine business executives. Risk was perceived to be related to the probability of failing to meet a certain target. Additionally, Conrath developed a descriptive model of decision making under risk, formulated mathematically as

$$C = f(L, p, e).$$

Here choice,  $C$ , is depicted as a function of  $L$ , the internal rate of return (or more generally, its utility) below which one is viewed as having failed;  $p$ , the probability that the return might be less than  $L$ , and  $e$ , the expected internal rate of return.

These two studies suggest that the overall variability of the return distribution (represented in most theoretical studies by means of the variance of the returns) does not have any important effect on capital budgeting decisions. They rather indicate that executives focus on the downside part of the return distribution. In order to shed some more light on this incongruence between theoretical hypotheses and empirical findings, we conducted an experiment, requiring preference judgments from business executives on hypothetical investment alternatives.

Other research questions to be analyzed in this study include: (1) How is information about returns (represented by ROI and payback period) and about other aspects of the investment (as number of additional personnel to

be hired and magnitude of the investment) combined in making investment-decisions? (2) Do upper management executives make different investment decisions than middle management executives?

However, before describing the experiment and its results we will discuss several methodological issues concerning the analysis of preference judgments.

## 2. METHOD FOR JUDGMENT ANALYSIS

The most commonly used methodology for examining how judges combine several information cues, on a given judgment task, into an overall judgment is a regression analysis. Such an analysis has been applied both across multiple decisions of a single judge or across decisions of multiple judges. This approach requires that the judgments have interval scale characteristics (i.e., order and difference between pairs of numbers associated with the judgment task have meaning). Examples of several judgment tasks studied within the traditional regression framework are as follows:

- (1) Predicting academic success (grade point average) of graduate students based on ten variables such as college grade point average, peer ratings and several self ratings (Wiggins and Kohen [22]).
- (2) Predicting the severity of Hodgkin's disease on a 9-point scale based on biopsy slides (Einhorn [5]).
- (3) Determining the amount willing to bid for playing a specific bet [Liechtenstein and Slovic [11]).
- (4) Rating of graduate students on a five point scale based on information available for three variables: the graduate Record

Exam, undergraduate grade point average, and an approximate rating of the quality of the institution at which the grade point average was obtained. (Dawes [4]).

- (5) Periodical decisions on production and workforce levels by production managers for an experimental task (McCann, Miller and Moskovitz [12]).

All of these judgment (decision making) tasks require basically an interdimensional evaluation strategy, i.e., evaluating each alternative separately in terms of an overall criterion. Studies by Russo and Rosen [17] and Russo and Doshier [16], however, found that for several multi alternative choice tasks, the majority of subjects did not use such a strategy. Indeed, they found that most subjects applied an intradimensional evaluation strategy, i.e. comparing alternatives on several choice dimensions, and then combining the results of these comparisons into preference judgments. (A similar choice strategy is the additive difference model suggested by Tversky [20]). In general their findings suggest that subjects (1) partition a multiple choice task into a sequence of paired comparisons, and (2) use a intradimensional evaluation strategy within these comparisons whenever dimensional comparisons are easy to perform. These results have been supported by Fidler and Atkin [7], who found that, for a given set of alternatives, subjects perceive interdimensional evaluation judgments to be significantly more difficult to make than paired comparison judgments. In addition, other studies requiring interdimensional evaluation strategies (e.g., Tversky and Kahneman [19]) found that subjects' conditional probability judgments were generally incorrect.

Given that interdimensional strategies appear to be difficult to apply, less likely to be used than intradimensional strategies, and incorrect, it is not

surprising that a linear model of the judges' responses generally predicts the "true judgment criterion" better than the actual judgments. Besides the fact that judgments made in terms of interval scale responses are likely to be incorrect, the variance explained by linear models is often very low. (e.g. Einhorn [5]). These results can be interpreted in two ways: either the models of the judgment process are not very good or the judgments are very "noisy".

In order to overcome some of these shortcomings we propose to estimate the judges' decision rules based on paired comparison preference judgments. Since pairwise evaluation strategies are simpler and more common we would expect to get better models of the judgment behavior than the studies cited above.

#### Model of Behavior

Before presenting our formal choice model we have to introduce a few definitions. First, denote  $s$

$$I = \{1, 2, \dots, n\}$$

a set of  $n$  stimuli for which dominance judgments have to be made. These  $n$  stimuli are assumed to be described by

$$J = \{1, 2, \dots, m\}$$

a set of  $m$  attributes. Then define as

$$X_i = (x_{i1}, x_{i2}, \dots, x_{im})$$

the  $i$ -th stimulus described in terms of  $m$  attribute dimensions. Furthermore let  $\Omega = \{(k, l): k, l \in I\}$  be the set of actual paired comparisons, and define

$$A_{kl} = (a_{kl1}, a_{kl2}, \dots, a_{klm}) = X_k - X_l \quad \forall (k, l) \in \Omega.$$

Now, our model can be formalized as follows. Each executive  $S$  (where  $1 \leq S \leq N_S$ , and  $N_S$  is the total number of judges) is assumed to have an utility function

$$U_{Sk\ell} = U_S(A_{kl}),$$

which is dependent on the attribute differences  $A_{kl}$  for a given binary choice between alternatives  $k$  and  $\ell$ . In this function  $|U_{Sk\ell}|$ , the absolute value of the utility function indicates the strength of preference for either alternative, while the sign of  $U_{Sk\ell}$  reflects whether  $k > \ell$ , i.e. alternative  $k$  is preferred to alternative  $\ell$  (when  $U_{Sk\ell} > 0$ ), or  $\ell > k$  (when  $U_{Sk\ell} < 0$ ). Furthermore, we assume that  $U_{Sk\ell}$  consists of a deterministic component  $V_{Sk\ell}$  which is a function of  $A_{kl}$  and a stochastic error term  $E_{Sk\ell}$  assumed to be independent of  $V_{Sk\ell}$  and capturing all misspecifications related with  $V_{Sk\ell}$ . Therefore, we can write

$$U_{Sk\ell} = V_{Sk\ell} + E_{Sk\ell} \quad (1)$$

where  $V_{Sk\ell}$  is assumed to be approximated by the linear function

$$V_{Sk\ell} = A_{kl} \beta.$$

In this equation  $\beta = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{pmatrix}$  represents a set of choice parameters which

determine the judges' preferences.

Although, our data collection technique results in  $U_{Sk\ell}$  being directly unobservable, we can obtain predictions of it based on estimates of these choice parameters.

In addition, we assume that  $V_{Sk\ell}$  is the same for a given population of judges. Then we can rewrite (1) for such a population as

$$U_{k\ell} = V_{k\ell} + E_{k\ell} \quad (1')$$

This assumption seems to be justified because several independent studies found that "given enough clinical judges, all possessing at least some validity, the most accurate predictions (in situations where criterion information is lacking) may well come from the composite judgments of the total group" (Goldberg [9], p. 431) (see also Wiggins and Kohen [22] for similar findings).

Under the assumption that  $V_{k\ell}$  is a linear function of  $A_{k\ell}$ , i.e.  $V_{k\ell} = A_{k\ell}\beta$ , we can rewrite this deterministic part of our choice model as

$$V_{k\ell} = A_{k\ell}\beta = (X_k - X_\ell)\beta = X_k\beta - X_\ell\beta = V_k - V_\ell.$$

In this equation  $V_k$  and  $V_\ell$  are equivalent to the deterministic component in linear utility functions of the form

$$U_i = V_i + e_i \quad \forall i \in I$$

where  $e_i$  is the stochastic component of the utility function associated with alternative  $i$ . This means that if  $V_{k\ell}$  is a linear function of  $A_{k\ell}$ , the inter- and intradimensional utility models are observationally equivalent. Therefore, we are also able to derive predicted utilities for the choice alternatives from our choice model, without requiring the decision maker to use a interdimensional evaluation strategy.

#### Estimation Techniques

Two techniques for estimating the  $\beta$ 's discussed above will be described now. The main differences between these two techniques lie in the algorithm used for determining the attribute weights and in the assumptions about the error terms.

A linear programming (LP) method proposed by Srinivasan and Shocker [18] is purely descriptive and makes no probabilistic assumptions about the error terms. Its goal is simply to estimate the  $\beta$ 's in such a way that the predictions of the model are as consistent as possible with the observed judgments. Formally this means that, for a given paired comparison judgment, the following relation should be fulfilled:

$$x_k \geq x_l \Rightarrow v_{kl} \geq 0 \quad \text{for all } (k, l) \in \Omega.$$

where  $v_{kl} \geq 0$  can be rewritten either as

$$(x_k - x_l)\beta \geq 0 \quad \text{or} \quad A_{kl}\beta \geq 0 \quad \text{for all } (k, l) \in \Omega.$$

Now let us define for all  $x_k \geq x_l$

$$(v_{kl})^- = \begin{cases} 0 & \text{for } v_{kl} \geq 0 \\ |v_{kl}| & \text{for } v_{kl} < 0 \end{cases}$$

as the extent to which  $v_k$  is smaller than  $v_l$ . Then for any particular set of weights  $\beta$  we can determine

$$\sum_{(k, l) \in \Omega} (v_{kl})^- = P$$

which is called the poorness of fit. Minimizing this poorness of fit measure with respect to  $\beta$  is therefore equivalent to the goal of making the  $v_{kl}$ 's as consistent as possible with the judgments.

Since by definition  $(v_{kl})^-$  is nonnegative, it follows that the trivial solution  $\beta = (0, 0, \dots, 0)$  would always minimize the poorness of fit measure. In order to preclude this solution from being feasible Srinivasan and Shocker

propose, without loss of generality, to impose the following constraint:

$$\sum_{(k,l) \in \Omega} (v_{kl}) = 1.$$

By defining  $z_{kl} = (v_{kl})^{-1}$  we can write the linear program for estimating the  $\beta$ 's proposed by Srinivasan and Shocker as follows:

$$\min \sum_{(k,l) \in \Omega} z_{kl}$$

such that

$$\begin{aligned} A_{kl}\beta + z_{kl} &\geq 0 && \text{for all } (k,l) \in \Omega \\ D\beta &= 1 && \text{where } D = \sum_{(k,l) \in \Omega} A_{kl} \\ z_{kl} &\geq 0 \\ \beta &\geq 0 \end{aligned}$$

As already mentioned above, this technique is only a descriptive method for estimating the  $\beta$ 's, without any probabilistic assumptions about the distribution of the error terms. Therefore it is also impossible to do any statistical analysis of the estimates. For this reason Fidler [6] proposed a maximum likelihood (ML) estimation technique for analyzing paired comparison judgments. The assumptions of the ML method can be summarized as follows:

$$\begin{aligned} U_{Sk\ell} &= A_{Sk\ell}\beta + E_{Sk\ell} \quad \text{where } E_{Sk\ell} \sim N(0, \sigma^2) \quad \text{and} \\ \text{Cov}(E_{Sk\ell}, E_{tmn}) &= \begin{cases} \sigma^2 & \text{for } k = m, \ell = n, S = t \\ 0 & \text{otherwise} \end{cases} \quad \left| \begin{array}{l} \forall k, \ell, m, n \in I \text{ and} \\ \forall S, t: 1 \leq S, t \leq N_S \end{array} \right. \quad (2) \end{aligned}$$

As indicated above  $U_{Sk\ell}$  is not directly observable but only a categorical variable  $Z$  indicating which stimulus is preferred in a given pairwise judgment.

The observed categorical dependent variable  $Z$  can be represented conveniently as a dummy variable which assumes the value 1 if  $X_k > X_l$  and the value 0 if  $X_l > X_k$ .<sup>1/</sup> From this it follows that

$$\begin{aligned} Z_{kl} = 0 & \Leftrightarrow U_{kl} < 0, \text{ and} \\ Z_{kl} = 1 & \Leftrightarrow U_{kl} > 0 \end{aligned} \quad (3)$$

Based on equations (2) and (3) we can write directly the probability function of the observed dependent variable  $Z$  as

$$\begin{aligned} \Pr(Z_{kl} = 0) &= \Pr(U_{kl} < 0) = \Pr(A_{kl}\beta + E_{kl} < 0) = \Pr(E_{kl} < -A_{kl}\beta) \\ &= \Phi\left(\frac{-A_{kl}\beta}{\sigma}\right) = 1 - \Phi\left(\frac{A_{kl}\beta}{\sigma}\right) \end{aligned} \quad (4a)$$

$$\begin{aligned} \Pr(Z_{kl} = 1) &= \Pr(U_{kl} > 0) = \Pr(A_{kl}\beta + E_{kl} > 0) = \Pr(E_{kl} > -A_{kl}\beta) \\ &= 1 - \Phi\left(\frac{-A_{kl}\beta}{\sigma}\right) = \Phi\left(\frac{A_{kl}\beta}{\sigma}\right) \end{aligned} \quad (4b)$$

where  $\Phi(t)$  represents the cumulative standard normal density function, i.e.,

$$\Phi(t) = \int_{-\infty}^t \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

and  $\Pr(A)$  is the probability of event  $A$ .

<sup>1/</sup> Since the subscript  $s$  for the different judges is not necessary for the further discussion of this technique it is deleted in all equations below.

The likelihood of  $Z$ , conditional on the parameters  $\beta$ , is then

$$L = L(Z|\beta_1, \dots, \beta_m) = \prod_{(k,l) \in \Omega} \{[\Phi(A_{kl}\beta)]^{Z_{kl}} [1-\Phi(A_{kl}\beta)]^{(1-Z_{kl})}\}$$

and the log likelihood function,  $L^*$ , is

$$L^* = \log L = \sum_{(k,l) \in \Omega} \{Z_{kl} \Phi(A_{kl}\beta) + (1-Z_{kl})[1-\Phi(A_{kl}\beta)]\} \quad (5)$$

By differentiating (5) with respect to the  $\beta$ 's and equating the partial derivatives to zero one obtains a nonlinear equation system from which the parameter estimates  $\hat{\beta}$  can be derived numerically by an iterative procedure (e.g. the Newton Raphson method). From a theoretical viewpoint the main advantage of the ML technique lies in the nice statistical properties of the ML estimators. Under rather general conditions the estimates are consistent and asymptotically efficient, and their asymptotic sampling distribution is known. In addition, hypotheses can be tested by using either this sampling distribution or by means of the likelihood ratio test. On the other hand, however, the LP method does not require any specific assumptions about the error terms, and therefore is more generally applicable. Therefore, in the result section we will compare the two estimation techniques in terms of their ability to predict actual judgments.

### 3. EXPERIMENTS

#### Alternatives

Twenty hypothetical investment projects were developed. Each of these alternatives was characterized in terms of four attribute dimensions: Discrete probability distribution of return on investment (ROI), payback period (PP), magnitude of the investment (MI), and number of additional personnel to be hired (AP). Each alternative was characterized by one value on each of these dimensions, except for ROI where three possible values with their associated probabilities were specified.

In order to analyze how executives evaluate probabilistic information, various parameters of this return distribution were calculated for each investment project. These parameters were as follows: the mean, variance and standard deviation of the ROI distribution, the probability of not meeting at target return, and the below target return semi variance.<sup>1/</sup>

### Subjects

The subjects were members of two different executive development programs. Experiments 1 and 2 consisted of  $n_1 = 29$  and  $n_2 = 33$  subjects respectively. Participation was voluntary. For both experiments, the participants were identified as either upper or middle management.

### Experimental Design

Each subject was given a questionnaire containing instructions and a random sample of thirty-four pairs of investment projects. This procedure resulted in approximately 5 subjects per experiment judging any particular pair. A preferable method would have presented all possible pairs (190) to all subjects, but this was deemed infeasible due to time and fatigue factors.

### Results

The presentation of the results of the experiments will be divided into four parts. First we will discuss differences in the results between the two estimation techniques described in the methodology section. Second we will examine the effects of management position. In the third section we will address the issue of whether executives tend to focus more on the downside or on the overall variation of the return distribution. Finally we will discuss differences between the two experiments.

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<sup>1/</sup> The numerical values of these variables for each alternative are described in Table 1.

The results of the two experiments will be presented in terms of the estimated attribute weights  $\hat{\beta}_1$ , descriptive criteria of fit, and the rank-order of the alternatives implied by the estimated utilities  $\hat{U}_1 = X_1 \hat{\beta}_1$ . Both, standardized and unstandardized weights are displayed in the tables because they have different interpretations. The unstandardized weights  $\hat{\beta}_j$  indicate the estimated change in utility for a unit change in the investment attribute  $j$ , while the standardized weights  $\hat{b}_j$ , can be interpreted as the relative partial saliences of the respective investment attributes. Mathematically  $\hat{b}_j$  is defined as:

$$\hat{b}_j = \frac{\hat{\beta}_j \sigma_j}{\sum_{j=1}^m |\hat{\beta}_j \sigma_j|}$$

where  $\hat{\beta}_j$  is the unstandardized weight,  $\sigma_j$  is the standard deviation and  $\hat{b}_j$  is the standardized weight of the  $j$ -th attribute dimension. The number of dimensions is denoted by  $m$  and  $| |$  refers to the absolute value symbol.

As the criterion of fit, we created two descriptive indices, which can be used to compare different choice models and different estimation techniques. These two indices are the percentage of correct individual and aggregate predictions. The percentage of correct individual predictions  $P_I$  is calculated as

$$P_I = 100 \cdot \frac{\text{Number of correct individual paired comparison predictions}}{\text{Total number of individual paired comparison judgments}}$$

An individual prediction of a given judge for paired comparison  $(k, l)$  is classified as correct when  $X_k > X_l$  and  $\hat{U}_{kl} > 0$  is fulfilled. On the other hand, the percentage of correct aggregate prediction  $P_A$  is defined as

$$P_A = 100 \cdot \frac{\text{Number of correct aggregate paired comparison predictions}}{\text{Total number of aggregate paired comparison judgments}}$$

An aggregate judgment in this context focuses on all individual judgments made for

a given paired comparison  $(k, l)$ . Then an aggregate prediction is called correct if the majority of judges prefers  $X_k$  to  $X_l$  and  $\hat{U}_{kl} > 0$ . Furthermore, since usually not all judges make identical judgments, the upper limit for  $P_I$  is less than 100. Therefore we are also reporting the percentage of potential correct individual predictions  $P_P$  which is the upper bound of  $P_I$  and also reflects the homogeneity among the judges' choices.

#### Comparison of the Estimates Obtained by Both the ML and the LP Technique

The evaluation of differences in the estimated utility functions between the two estimation techniques will be presented only for experiment 1 because the results from experiment 2 are highly similar. Of the 29 participants in experiment 1, 20 were classified as middle management and 9 as upper management.

Table 2 presents the Model 1 utility functions estimated by the LP method for both management groups, while those obtained by the ML method are presented in Table 3. Model 1 characterizes the probability distribution of ROI by its mean  $\mu$  and its standard deviation  $\sigma$ . In the statistical literature  $\sigma^2$  and  $\sigma$  are used interchangeably because there is a one to one relationship between the two measures. From an behavioral point of view, however, there is a difference between  $\sigma$  and  $\sigma^2$  because they imply a different functional form of the individual utility functions. Therefore, we also estimated a variant of Model 1 by using  $\sigma^2$  instead of  $\sigma$ . Although the latter variant resulted in slightly worse predictions, the results of both were very similar. Therefore, we have only reported the results for Model 1.

A comparison of the parameter estimates of the utility function and the rankordering of the alternatives derived from the estimated utilities reveals that there are only slight differences in the results between these two estimation techniques. This is also supported by the correlation coefficients (1) and (2) in Table 9 between predicted utilities derived from the parameter estimates

by both methods. However, from a theoretical point of view, the ML method is more attractive because it does not force  $m-1$  pairs of stimuli to have the same value on the utility scale (see Fidler [6] for a more thorough discussion of this deficiency) and, in addition, it allows statistical analysis of the estimates. Furthermore, the ML method consistently predicted more (although only slightly more) actual judgments. This predictive superiority of the ML method probably results from the lack of "forced ties" between alternatives. For these reasons, we will only consider the ML method in the remainder of the paper.

#### Comparison of Upper and Middle Management Judgments

Based on our prior beliefs, we expected positive attribute weights for ROI mean, and negative weights for PP, ROI- $\sigma$ , and AP both for upper and middle management executives. The reasons for the hypothesized signs of these attribute weights are quite straightforward and therefore are not further elaborated. For the sign of MI we did not have any strong prior expectations, because there might not be a monotone relationship between MI and utility. For example, we would expect for low ROI's, MI to have a negative influence on utility and a positive influence for higher ROI's.

We had no strong prior beliefs related to whether upper and middle management executives have different preferences for investment alternatives. Bower [1] for example has argued that managers at the business level might have a more short run view of problems because they move every two to three years but on the other hand might also have more of a long run view because they are not subjected to public and stockholder concern with quarterly earnings per share.

As can be seen in Tables 3 and 4, the coefficient estimates have the expected signs and MI has a positive sign. In order to test for a nonmonotone

relationship between MI and utility, we divided the stimuli into two groups based on the mean ROI. Then we analyzed each of these subgroups separately, but also found a positive relationship between MI and utility.

Significance tests of the estimated coefficients show that in all four management groups the null hypothesis  $H_0: \beta_1 = 0$  cannot be accepted at the significance level  $\alpha = 0.01$  for ROI- $\mu$ , PP, and MI. For ROI- $\sigma$  and AP, on the other  $H_0: \beta_1 = 0$  cannot be rejected sometimes ( $\alpha = .05$ ).

A comparison of standardized weights shows that ROI- $\mu$  and PP have the highest partial effects on the choices between pairs of alternatives. This result coincides with the findings of the survey studies cited at the beginning of this paper. Compared to these two variables, the other three attributes seem to have a relatively minor effect on the judgments.

Since the estimated attribute weights are very similar for upper and middle management in both experiments it is not surprising that the rankorder of the alternatives based on the predicted utilities is not very different. This is also confirmed by the correlation coefficients of  $r_1 = .98$  and  $r_2 = .97$  between the predicted utilities of upper and middle management executives for experiments 1 and 2 (see Table 9.1). In order to test whether the choice models for upper and middle management derived from the pair comparison judgments were different, we performed a likelihood ratio (Chi-Square) test for each experiment. The results of these two Chi-Square tests are given in equations (1) and (2) of Table 8. For both experiments the test statistics indicate that the  $H_0$ : upper management has the same utility function as middle management, cannot be rejected at the confidence level  $\alpha = .25$ . Therefore we will not distinguish between upper and middle management executives in the following analysis which examines whether downside variation of the return distribution influences judgments more than overall variations.

Downside vs. Overall Variations of the Return Distribution

Several authors (e.g. Mao [13], and Conrath [3]) have recently proposed that business executives focus on the downside part of the return distribution rather than on the total variation. In order to test this proposition, we constructed two variables reflecting only the downside part of the return distribution. These two variables were the below target return semi-variance ( $\sigma_T^2$ ) and the probability of not achieving the target return ( $P_T$ ). In general,

$$\sigma_T^2 = E(x-T)^2 \text{ for } x \leq T$$

where  $T$  is the target return and  $E$  is the expectation operator, and

$$P_T = \Pr(x \leq T).$$

In order to calculate  $\sigma_T^2$  and  $P_T$  one has to specify the target return  $T$ . Since we did not have any strong prior beliefs about the size of the target return, we calculated  $\sigma_T^2$  and  $P_T$  for target returns of 10%, 12%, 14% and 16% and included each different  $\sigma_T^2$  and  $P_T$  variable (one at a time) to the Model 1 variables. By means of this procedure we could see which of these new variables characterizes the downside part of the return distribution best. The results of this procedure suggested that inclusion of  $\sigma_T^2$  increased the predictive power in terms of  $P_I$  and  $P_A$ . Furthermore  $T = 12\%$  was the target return which maximized the likelihood function for the different  $T$ 's and had the highest indices of fit. Based on these results our Model 2 presented in Table 6 contains, in addition to the variables in Model 1, also  $\sigma_T^2$  for  $T = 12\%$ .

The Model 2 results for both experiments show that the partial importance weights of  $\sigma_T^2$  are much higher than those of  $ROI-\sigma$ . Furthermore, tests of the

hypothesis  $H_0: \beta_1 = 0$  indicate that this hypothesis cannot be accepted ( $\alpha = .005$ ) for the  $\sigma_T^2$  coefficient estimates, but it cannot be rejected ( $\alpha = .25$ ) for the ROI- $\sigma$  coefficient estimates. The indices  $P_I$  and  $P_A$  which are about 1% higher for Model 2 than for Model 1 also indicate that Model 2 is a somewhat better representation of the judgments. These results, obtained from a much larger sample of executives compared to the studies by Conrath [3] and Mao [13], strongly support and advance their findings of how managers evaluate probabilistic information about the return distribution. Thus it becomes more and more evident that the overall variation of the return distribution is not a good construct for explaining investment-decisions.

#### Differences in Judgments between Experiment 1 and 2

By comparing the results of the judgment analysis between experiment 1 and 2 we see that both the coefficient estimates and the rankorder of the alternatives are almost identical. This similarity is reflected by a Chi-Square test of  $H_0$ : the attribute weights are equal for the two experiments. (see Table 8, equation (3)). The result of this test indicates that  $H_0$  cannot be rejected at the significance level  $\alpha = .3$ . The correlation coefficient  $r = .98$  (see Table 9, equation (5)) between the predicted utilities of experiment 1 and 2 also upports the results of the Chi-Square test.

These results combined with the results obtained from the separate analysis of the upper and middle management judgments indicate that there are no statistically significant differences between the linear decision rules inferred from the paired comparison judgments of various groupings of judges. However, this similarity of the judgment is unlikely due to effects of the participation in the executive development program because both experiments have been conducted at the beginning of each program, before any lectures on capital budgeting were given. It rather indicates that business executives have similar preferences with respect to outcomes of investment decisions.

## DISCUSSION

The results of this study confirm and extend findings from other empirical studies of capital budgeting decisions. It confirms the results of several other studies that (i) ROI and PP are the most important investment characteristics and (ii) that downside variation of the return distribution has a stronger influence on investment decisions than overall variation. The approach used for analyzing capital budgeting decisions in this study, however, is different and allows a more rigorous analysis of the decision process. First, we postulated a specific choice model and second we statistically estimated its parameters based on actual decisions. This allows us to determine the partial saliences of the investment characteristics and the combination rule for combining the information cues into preference judgments. Although we expected ROI and PP to be the most important investment characteristics, we were surprised that they are almost equally important. This result is compatible with explanations that payback period is viewed as a measure of (1) the risk of lost opportunities (Byrne, Charnes, Cooper, and Kortanek [2]) and (2) the liquidity and uncertainty of an asset (Weingartner [21]).

The methodology for analyzing organizational decisions, proposed in this paper is different from most other studies. The judgments required from subjects are less difficult (yes-no decisions on pairs of alternatives instead of interval scale responses) and therefore most likely more accurate. The underlying assumption of this hypothesis is that tradeoff of quality (accuracy) of information against quantity (how much different are the alternatives) enables us to obtain a better model of the judgment process and better predictions of the "true" criterion variable. However, this hypothesis has not been tested yet, but efforts are currently underway to investigate this assumption.

Based on the models presented in Tables 3 through 7 one can see that the predictive quality of the model, as measured by  $P_I$  and  $P_A$ , increases with the number of judges. With increasing number of judges,  $P_I$  comes closer to  $P_p$  while  $P_A$  approaches 100. Furthermore, our results show that, although the criteria of fit increase with the number of judges the model, (in terms of the linear decision rule) on the other hand, does not change significantly with more judges. This seems to support, as a rule of thumb, that approximately two judgments for each paired comparison (which corresponds roughly to a group of 10 judges in this experiment) should be sufficient to estimate the inferred linear decision rule of a homogenous group of judges.

In general, our methodology can also be used for analyzing individual judgments and to infer the decision strategy used by one decision maker. The inferred decision strategies, then could be used for determining individual differences among individuals and might help to develop training programs to minimize individual differences in decision making. However, the most important potential application of this technique is as a decision making aid. Once the attribute weights have been estimated they can be used to rankorder not only the alternatives for which the decisions have been made, but also others in similar decision situations. Depending on the importance of the decision, the predicted utilities can be used either as the decision criterion or as a screening technique in order to separate the "good" alternatives from the rest. Then management would have to evaluate only a reduced set of alternatives and could therefore investigate each "good" alternative more thoroughly. The question remains whose judgments (one expert or a group of experts) should be used for determining the attribute weights. For this issue, of course, there exists no universal answer (unless one knows the best expert in the field with certainty),

but there exists some evidence that, in general, the model derived from judgments of a group of experts is a better predictor of the true criterion than a model derived from the decisions of one expert (cf. Goldberg [9]). Therefore, it might be a reasonable strategy to use the judgments of a committee as a basis from which the decision rule is inferred.

The methodology proposed in this paper for analyzing preferences is based on evidence generated by studies of individual choice behavior. Empirical studies will have to show whether linear decision rules derived from paired comparison judgments are superior to the ones obtained from rankorder or interval scale responses. Additionally it will have to be tested whether some of the findings such as the bootstrapping phenomenon or the superiority of the composite judge, obtained in the traditional judgment studies are also valid if the type of judgment to be made is less complex. This type of analysis would show how studies of the cognitive aspects of the decision making process could be applied to improve organizational decisions and to reduce the cognitive strain of executives by freeing them from making time consuming routine decisions for which no quantitative criteria are readily available.

Table 1

Stimulus-Attribute Matrix of the Investment Projects

<u>Project Number</u>	<u>Payback Period</u>	<u>Amount of Investment</u>	<u>Additional Personnel</u>	<u>ROI Mean</u>	<u>ROI Standard Deviation</u>	<u>ROI Semi- variance</u>
1	4.00	100.00	3.00	10.40	1.95	5.6
2	2.00	40.00	2.00	16.80	4.07	0.8
3	5.00	75.00	6.00	9.20	2.57	13.6
4	7.00	150.00	2.00	13.20	3.26	1.2
5	6.00	70.00	8.00	17.90	2.02	0.
6	1.00	20.00	0.00	19.60	2.32	0.
7	6.00	100.00	9.00	16.60	4.20	0.8
8	4.00	80.00	4.00	11.60	2.37	3.1
9	3.00	60.00	7.00	11.40	3.10	3.2
10	8.00	50.00	1.00	10.20	2.24	7.4
11	4.00	60.00	5.00	14.30	2.10	0.1
12	1.00	90.00	6.00	11.60	1.55	2.1
13	8.00	150.00	3.00	16.10	1.92	0.1
14	4.00	70.00	8.00	17.60	2.86	0.
15	7.00	200.00	2.00	12.00	2.05	2.7
16	8.00	100.00	5.00	12.20	1.41	0.8
17	3.00	20.00	2.00	10.40	2.49	8.0
18	5.00	75.00	7.00	13.60	1.95	0.8
19	3.00	250.00	9.00	13.20	2.57	0.4
20	9.00	150.00	5.00	12.90	2.07	1.2
Mean	4.9	95.5	4.7	13.5	2.45	2.6
Standard Deviation	2.4	58.6	2.75	2.96	0.74	3.54

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Table 2

Standardized and Unstandardized Attribute Weights  
Estimated by the LP Method for Experiment 1

	Upper Management Standardized Weights	Middle Management Standardized Weights	Upper Management Unstandardized Weights	Middle Management Unstandardized Weights
Payback Period	-.30	-.32	-.12	-.13
Magnitude of Investment	.08	.10	.0014	.0017
Additional Personnel	-.13	-.16	-.048	-.059
ROI-Mean	.41	.38	.14	.13
ROI-Standard Dev.	-.08	-.04	-.11	-.05
Percentage of Correct Aggregate Predictions	75.1	71.6		
Percentage of Correct Individual Predictions	79.6	72.7		
Percentage of Potential Correct Individual Predictions	86.2	81.0		

Rankorder of the Investment Projects Implied by these Weights

<u>Rank</u>	Upper Management <u>Project Number</u>	Middle Management <u>Project Number</u>
1	6	6
2	2	2
3	14	14
4	5	12
5	12	5
6	11	19
7	13	11
8	19	13
9	18	7
10	7	8
11	8	4
12	15	15
13	1	17
14	4	18
15	17	1
16	9	9
17	16	20
18	20	16
19	10	3
20	3	10

○ Indicates ties

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Table 3

Standardized and Unstandardized Attribute Weights  
Estimated by the ML Method for Experiment 1

	Upper Man. Stand. W.	Middle Man. Stand. W.	Upper Man. Unstand. W.	Standard Error	Middle Man. Unstand. W.	Standard Error
Payback Period	-.30	-.33	-.21	.03	-.16	.02
Magnitude of Investment	.10	.16	.0028	.001	.0031	.0007
Additional Personnel	-.04	-.07	-.023	.02	-.028	.015
ROI-Mean	.46	.40	.26	.03	.16	.015
ROI-Standard Dev.	-.11	-.04	-.25	.1	-.07	.05
Percentage of Correct Aggregate Predictions			76.4		72.6	
Percentage of Correct Individual Predictions			80.6		73.6	
Percentage of Potential Correct Individual Predictions			86.2		81.0	

Rankorder of the Investment Projects Implied by these Weights

Rank	Upper Management Project Number	Middle Management Project Number
1	6	6
2	14	2
3	2	19
4	5	14
5	19	5
6	12	12
7	11	11
8	13	13
9	7	7
10	18	18
11	8	15
12	15	8
13	1	4
14	9	9
15	4	1
16	17	17
17	16	20
18	20	16
19	3	3
20	10	10

Table 4

Standard and Unstandardized Attribute Weights for Experiment 2

	Upper. Man. Stand. W.	Middle Man. Stand. W.	Upper Man. Unstand. W.	Standard Error	Middle Man. Unstand. W.	Standard Error
Payback Period	-.28	-.27	-.15	.03	-.17	.02
Magnitude of Investment	.25	.18	.0055	.001	.0046	.0007
Additional Personnel	-.05	-.11	-.022	.02	-.061	.01
ROI-Mean	.40	.39	.17	.02	.20	.02
ROI-Standard Dev.	-.01	-.05	-.025	.08	-.10	.05
Percentage of Correct Aggregate Predictions			72.0		76.8	
Percentage of Correct Individual Predictions			75.2		75.6	
Percentage of Potential Correct Individual Predictions			87.1		80.9	

Rankorder of the Investment Projects Implied by these Weights

Rank	Upper Management Project Number	Middle Management Project Number
1	6	6
2	19	2
3	2	19
4	14	14
5	5	5
6	13	13
7	7	12
8	12	11
9	11	15
10	15	7
11	4	4
12	18	18
13	8	8
14	1	1
15	9	9
16	20	17
17	17	20
18	16	16
19	3	3
20	10	10

Table 5

Standardized and Unstandardized Attribute Weights of Pooled Upper and Middle Management Judgments for Experiments 1 and 2

	Experiment 1 Stand. Weights	Experiment 2 Stand. Weights	Experiment 1		Experiment 2	
			Unst. W.	Stand. Error	Unst. W.	Stand. Error
Payback Period	-.32	-.30	-.17	.016	-.21	.034
Magnitude of Investment	.14	.10	.003	.0006	.003	.001
Additional Personnel	-.06	-.04	-.03	.013	-.023	.025
ROI-Mean	.42	.46	.18	.013	.27	.03
ROI-Stand. Dev.	-.06	-.11	-.10	.05	-.25	.10
Percentage of Correct Aggregate Predictions			84.2		76.4	
Percentage of Correct Individual Predictions			76.2		80.6	
Percentage of Potential Correct Individual Predictions			80.2		86.2	

Rankorder of the Investment Projects Implied by these Weights

Rank	Experiment 1		Experiment 2	
	Project Number	Project Number	Project Number	Project Number
1	6	6	6	6
2	2	14	14	14
3	14	2	2	2
4	19	5	5	5
5	5	19	19	19
6	12	12	12	12
7	11	11	11	11
8	13	13	13	13
9	7	7	7	7
10	18	18	18	18
11	15	15	15	15
12	8	8	8	8
13	4	15	15	15
14	9	1	1	1
15	1	9	9	9
16	17	4	4	4
17	20	17	17	17
18	16	16	16	16
19	3	20	20	20
20	10	3	3	3
		10	10	10

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Table 6

Standardized and Unstandardized Attribute Weights of Pooled  
Upper and Middle Management Judgments for Experiments 1 and 2

	Experiment 1		Experiment 2		Experiment 1		Experiment 2	
	Stand. Weights	Stand. Weights	Stand. Weights	Stand. Weights	Unst. W.	Stand. Error	Unst. W.	Stand. Error
Payback Period	-.32	-.28	.17	.016	-.17	.016	-.16	.015
Magnitude of Investment	.10	.17	.10	.0007	.0021	.0007	.0041	.0006
Additional Personnel	-.075	-.10	.30	.013	-.034	.013	-.053	.012
ROI-Mean	.31	.30	-.02	.020	.13	.020	.15	.020
ROI-Stand. Dev.	-.033	-.02	-.13	.05	-.056	.05	-.04	.05
ROI-Semi-Variance	-.17	-.13		.02	-.06	.02	-.05	.017
Percentage of Correct Aggregate Predictions					86.3		83.4	
Percentage of Correct Individual Predictions					77.2		76.4	
Percentage of Potential Correct Individual Predictions					80.2		79.2	

Rankorder of the Investment Projects Implied by these Weights

Rank	Experiment 1		Experiment 2	
	Project Number	Project Number	Project Number	Project Number
1	6	6	6	6
2	2	2	2	2
3	14	14	19	19
4	19	19	14	14
5	12	12	13	13
6	5	5	5	5
7	11	11	12	12
8	13	13	11	11
9	7	7	7	7
10	18	18	4	4
11	8	8	15	15
12	4	4	18	18
13	9	9	8	8
14	15	15	9	9
15	1	1	1	1
16	17	17	20	20
17	16	16	16	16
18	20	20	17	17
19	10	10	10	10
20	3	3	3	3

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Table 7

Standardized and Unstandardized Attribute Weights  
for Pooled Experiments 1 and 2

	Standardized Weights	Unstandardized Weights	Standard Error
Payback Period	-.30	-.16	.01
Magnitude of Investment	.14	.0031	.00046
Additional Personnel	-.09	-.044	.009
ROI-Mean	.30	.14	.014
ROI-Stand. Dev.	-.02	-.045	.03
ROI-Semi-Variance	-.15	-.056	.012
Percentage of Correct Aggregate Predictions		92.6	
Percentage of Correct Individual Predictions		76.8	
Percentage of Potential Correct Individual Predictions		77.9	

Rankorder of the Investment Projects Implied by these Weights

Rank	Project Number
1	6
2	2
3	19
4	14
5	12
6	5
7	11
8	13
9	7
10	18
11	4
12	15
13	8
14	9
15	1
16	20
17	17
18	16
19	10
20	3

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Table 8

Likelihood Ratio (Chi-Square) Tests

A. Tests for differences between upper and middle management

$$1) H_0: \beta_{U1} = \beta_{M1} \quad x^2 = 4.96 \quad v = 5$$

$$2) H_0: \beta_{U2} = \beta_{M2} \quad x^2 = 4.54 \quad v = 5$$

B. Test for differences between experiments 1 and 2

$$3) H_0: \beta_1 = \beta_2 \quad x^2 = 6.8 \quad v = 6$$

$x^2$  = value of the Chi-Square test

$v$  = degrees of freedom of  $x^2$  distribution

$\beta_{U1}$  = upper management weights for experiment 1

$\beta_{U2}$  = Upper management weights for experiment 2

$\beta_{M1}$  = middle management weights for experiment 1

$\beta_{M2}$  = middle management weights for experiment 2

$\beta_1$  = weights of all executives for experiment 1

$\beta_2$  = weights of all executives for experiment 2

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Table 9

Correlation Coefficients Between Predicted Utilities  $\hat{U}$

- (1)  $r_{\hat{U}_{U_{ML}} \hat{U}_{U_{LP}}} = 0.979$  where  $U_{ML}$  = upper management ML method estimates  
 $U_{LP}$  = upper management LP method estimates
- (2)  $r_{\hat{U}_{M_{ML}} \hat{U}_{M_{LP}}} = 0.970$  where  $M_{ML}$  = middle management ML method estimates  
 $M_{LP}$  = middle management LP method estimates
- (3)  $r_{\hat{U}_{U_1} \hat{U}_{M_1}} = .984$  where  $U_1$  = upper management experiment 1 estimates  
 $M_1$  = middle management experiment 1 estimates
- (4)  $r_{\hat{U}_{U_2} \hat{U}_{M_2}} = .974$  where  $U_2$  = upper management experiment 2 estimates  
 $M_2$  = middle management experiment 2 estimates
- (5)  $r_{\hat{U}_1 \hat{U}_2} = .986$  where 1 = experiment 1 estimates  
 2 = experiment 2 estimates

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expected payback period for the investment. Five conclusions are demonstrated based on two independent experiments with business executives:

- (1) Mean return on investment, and payback period, are the most important investment characteristics;
- (2) Upper and middle management executives have almost identical preference structures;
- (3) Downside variation of the return distribution has a stronger influence on investment decisions than overall variations;
- (4) Usefulness of this methodology for (i) analyzing preference judgments of individual executives; (ii) training purposes; and (iii) as an aid to organizational decision making; and
- (5) Both data analysis techniques give highly similar conclusions.

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